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Research article

Modeling the Impact of some Macroeconomic Variables on Unemployment Rate in Africa

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ABSTRACT

Unemployment remains a challenging socio-economic problem in Africa. This study used panel data to investigate the impact of some macroeconomic variables on unemployment rate in Africa with data from World Development Indicators ranging from 1994 to 2023 on 49 Africa countries. Traditional panel models and machine learning models were implemented. The Hausman test revealed that, the fixed effect model was the best traditional model and the multilayer perceptron model was recorded as the overall best model. From the MLP model, the three most significant variables that affect the unemployment rate are agriculture, population growth, which have a negative relationship, and current account balance, with a positive relationship. The study recommends that better policies, such as start-up capital for youth in agriculture, and modern machines should be made available, incentives for a few families, and restrictions on the maximum number of children a family can have to regulate population growth.

1. Introduction

Unemployment has been one of the major socio-economic problems that is affecting most countries. It is defined by world development Indicators (WDI) as the portion of the active labor force that does not have work but available for and actively seeking employment [25]. It is computed as a percentage of the total labour force, using the International Labour Organization's methodology. Globally, the unemployment rate for 2019, 2020, 2021 and 2022 were 5.583%, 6.585%, 6.034% and 5.265% respectively according to the Word Development Indicators [25].

In the context of Africa, the aggregated rate of unemployment as at the end of 2020 was 7.1% which increased to 7.19% at the end of 2021. The rate of unemployment has been around 7% over the years [9]. In the year 2022 and 2023, there was a constant unemployment rate of 7.11% within the Africa continent [9]. Based on regions, Southern Africa recorded the highest rate of unemployment with a 32.2% of it labour force unemployed. North Africa, West Africa, Central Africa and East Africa had the least recorded unemployment rate of 12.6%, 6.8%, 6.2% and 4.7% respectively [23].
In contrast with the unemployment rate around the western world, many studies such as [17] and [4] concluded that, Africa have high unemployment rate as compared to most of the continents around the globe. For instance, as at the end of 2020, 2021, 2022 and 2023, the unemployment rate around the globe were 8.23%, 5.59%, 3.83% and 3.82% respectively [12]. This result confirms that the unemployment rate in North America has been reducing gradually over the years as compared to Africa which keeps on increasing.

Similarly, on the basis of gender, woman dominate the unemployment rate in Africa. From the total unemployment rate in 2020, Southern Africa recorded 34.1% and 30.7% for both female and male respectively whilst North Africa also recorded 23.4% and 9.3% unemployment rate for both female and male respectively. On the other hand, West Africa recorded 6.4% and 7.1% unemployment rate for both female and male respectively whilst Central Africa recorded 6.3% and 6.1% unemployment rate for both female and male respectively. Again, East Africa has the minimum rate of unemployment of 5.4% and 4% for both female and male respectively [24]. From the [12], the unemployment rate within North Africa is highly dominated by female. This is as a result of inequality of employment opportunities made available for both male and female. Most often in Africa, females are deprive of engaging in certain fields of employment within the continent as compared to that of the Western world.

Globally, Africa is noted to be the second largest continent with regards to size but is the world's poorest region with low economic development coupled with social and political crisis [19]. However, Africa is considered the richest continent in the world with regards to mineral deposit such as oil, platinum, gold, chromium, diamond, manganese, iron ore, uranium etc. Despite having numerous natural and human resources, African countries remains the most impoverished and underdeveloped in the world [19].

[1] concluded that, although several intervention programs have been implemented in Africa to reduce unemployment rate, little have been achieved. Example is the Regional Coordination Mechanism (RCM) and the Evidence and Gap Map (EGM) which focuses on any programs, initiatives, or interventions that help young people in obtaining and maintaining employment. The United Nations Development Programme (UNDP) Sustainable Development Goals (SDG) 8 and 10 are designed to fight unemployment and inequality in all forms by the end of 2030 [21].

According to the 2024 United Nations (UN) population report, Africa will account for over half of global population growth by 2050 [18]. With that, the population of sub−Saharan Africa is estimated to double by 2050. Empirical studies by [8] and [5] concluded that population growth has a negative effect on employment. [8] in their study concluded that the continues increase in the population of developing countries will increase the labour force which will end up increasing unemployment. [11] confirmed that inflation, value of the local currency, and its performance are key determinants for investing in the financial market. It was added that in the long run inflation will affect the investment capital of firms which will make them to reduce their production size by resulting in the laying off workers. This study used both traditional panel models and machine learning models to investigate the impact of the selected macroeconomic variables on unemployment rate in African.

2. Methodology

2.1. Data Source and Variables in the Study

The study sourced annual data from the (WDI) ranges from 1994 to 2023 on 49 Africa countries with a total data points of 17,028 which has been treated in this study as a panel data analysis. Twelve (12) macroeconomic variables from the 49 Africa countries were considered.
The countries that were used are Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Dem. Rep. of Congo, Congo Rep., Cote d'Ivoire, Djibouti, Equatorial Guinea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, South Africa, Sudan, Tanzania, Togo, Tunisia, Uganda, Zambia and Zimbabwe.
Dependent variable; unemployment rate (UNEMP).
Independent variable;
The various independent variables used are general government final consumption expenditure (GOVCONS, % of GDP), foreign direct investment (FDI, % of GDP), agriculture(forestry, and fishing, value added % of GDP) (AGRIC), population growth (POPG, annual %), personal remittances, received (PWKR, % of GDP), official exchange rate (EXR, LCU per US$, period average), current account balance (CAB, % of GDP), trade (TRD, % of GDP), inflation, GDP deflator (INF, annual %), final consumption expenditure (FINCONS, % of GDP), gross savings (% of GDP).

2.2. Fixed effect regression model

The fixed effects enables us to capture the individual characteristics of entities involve in the study and manage for their impact on the outcome of interest. The panel regression model is given by;

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_i + u_{it}, \tag{1}$$

where t is the year, i is the individual, Z_i are unobserved time-invariant heterogeneity across the entity

$$i, i = 1, 2, ..., n \tag{2}$$

This aim is to estimate β_1, the effect on Y_i of a change in X_i holding Z_i constant.

2.3. Main assumptions of fixed effects model

1. The error term u_{it} has conditional mean zero, that is, $E\ (u_{it} \mid X_{i1}\ X_{i2},...,X_{it} = 0)$.
2. The X_{i1}, X_{i2} , X_{it},u_{i1}...,u_{iT}, $i = 1, ..., n$ are i.i.d. draws from their joint distribution.
3. There is no perfect multicollinearity.
4. Large outliers are unlikely, i.e., (X_{it}, u_{it}) have nonzero finite fourth moments.

2.4. Random effect regression model

Random effects models are used to account for variability and differences between various entities within, as opposed to fixed effects, which capture characteristics that stay consistent across observations.

Random effects estimator are reliable under the assumption that individual characteristics are exogenous. The random effect model account for the unobserved heterogeneity. Thus, it permit for the inclusion of unobserved factors that vary across entities within a data set and mathematically represented as:

$$Y_i = \beta_i X_i + \alpha + (\mu_i + \epsilon_i), \tag{3}$$

where

$$i = 1, 2, 3, ...n, \tag{4}$$

Y_i is the dependent variable, $\beta_i X_i$ is the fixed effect component where X_i is made of the individual predictors used in the study while β is their corresponding coefficients, α is the random effect for the group, it main purpose is to capture the group specific variation that is not explained by the fixed effects. ϵ_i represents the residuals which are unable to be explained by both the fixed effects and random effects models and μ_i is the error term for entity i at time t.

2.5. Neural Network

Neural networks (NNs) are very useful for assessing complex non−linear relationship. [7] confirmed that artificial neural networks are built on the fundamental ideas of how the human brain operates. It has been demonstrated that neural networks often accurately forecast and approximate complex nonlinear functions. However, they are commonly criticized as being incomprehensible or a ”black box” because they do not permit descriptions of the relationships in the data. However, a number of studies conducted have tried to make the output more interpretable [3]. It can be use for predicting, classifying, control systems, decision making and optimization.

2.5.1. Activation functions (AF)

Artificial neural network (ANN) uses AF in achieving the output. Some activation functions are;

1. **Sigmoid(Logistic AF)**: This activation function is use for models which we intend to forecast the probability as output. Mathematically it is given as;

$$\phi(z) = \frac{1}{1 + e^{-z}}, \tag{5}$$

where ;
$z = \sum_{i=1}^{n} w_i x + b_i$, x_i are the input signals, w_i are weights associated to the input signal and b_i are the biases.

2. **Hyperbolic tangent AF**: This uses the hyperbolic function and is often use when modeling non-linear relationship between variables. One major benefit is that, the fact that the zero inputs will be mapped close to zero in the tanh graph and the negative inputs will be highly negative. It values ranges between -1 and 1. Users always preferred it over the sigmoid activation function due to it unique property of capturing the negative aspect as well as the positive part. Mathematically is represented as

$$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}, \tag{6}$$

where $z = \sum_{i=1}^{n} w_i x + b_i$, x_i are the input signals, w_i are weights associated to the input signal and b_i are the biases

2.6. Recurrent neural network(RNN)

RNN is a non-parametric neural network type, and tailored for sequential data. Unlike the traditional feedforward neural networks that process each input independently, RNNs can remember previous inputs. This is done by feeding the output from one step back into the network in the next step. Recurrent networks allow signals to move in both directions using loops. Most studies used RNNs in addressing temporal dependencies in sequential time series data. In spite of it advantages, it has problems associated with training the long term data dependencies [22]. RNNs are trained by a backpropagation algorithm. The hidden state h_t at time step t is calculated based on the current input x_t and the previous hidden state h_{t-1}. The hidden state calculation is represented as;

$$h_t = f(UX_t + Wh_{t-1} + b_h), \tag{7}$$

where b_h is the bias vector for the hidden layer, W is the weight matrix for the hidden layer, h_t is the hidden state at time step t, f is a nonlinear activation function.

2.7. Multi-layer perceptron regression model (MLP)

The single-layer perceptron model, as the first form of MLP, is made up of only two layers, the input layer and the output layer. Because it only has one neuron per adjustable synaptic weight and bias, this constraint often arises during implementation [13].
The output of the Kth output layer neuron is;

$$y_k = f(\sum_{i=1}^{n} w_{ik}x_i - \theta_k), \tag{8}$$

where $x_1, x_2, ..., x_n$ is the input data and $\sum_{i=1}^{n} w_{ik}x_i, k = 1, 2, ..., n$ represent the total amount of information it receives.
To further improve the learning ability of neural networks to solve more practical problems, the multilayer The perceptron model with hidden layers, which evolved from the single-layer perceptron, was created.

2.8. Extreme gradient boosting regression model

This is an ensemble model that is based on boosting. Boosting is the process of fitting data by using a first model, then creating a second model based on the first one that aims to correct the first model's inaccurate findings, and so on until a better result is achieved. These individual models are also refer to week models.
The algorithm of the XGBoost includes the following phases for the input data;
Step 1: Set a fixed value as the model's starting point;

$$F_0(x) = argmin_y \sum_{i=1}^{n} L(Y, \bar{y}), \tag{9}$$

where Y is the observed value, and $\bar{y}$ is the predicted value. $F_0(x)$ is the average of the observed values.
Step 2: For $m = 1$ to M :

- Calculate

$$\bar{y}_{im} = -[\frac{\delta \mathbf{L}(\mathbf{Y}, \mathbf{F}(\mathbf{x_i}))}{\delta \mathbf{F}(\mathbf{x_i})}]_{F(x)=F_{m-1}(x)}, i = 1, 2, ..., n. \tag{10}$$

- Adjust a tree for regression to the $\bar{y}_{im}$ values and generate terminal regions R_{jm} for $j = 1, ...jm$.
- For $j = 1, ..., jm$, calculate;

$$\bar{y}_{im} = argmin_y \sum_{x_i \epsilon R_{ij}}^{n} L(Y_i, F_{m-1}(x_i) + \bar{y}). \tag{11}$$

- Modify

$$F_m(x) = F_{m-1}(x) + \alpha \sum_{j=1}^{Jm} \bar{y}_m I(x \epsilon R_{jm}), \tag{12}$$

where α is the learning rate. By changing the learning rate, the user can alter the behavior of the loss functions used. This feature improves the model's flexibility while reducing the overfitting issue through the lessons learned during the slower iterations [6].

Step 3: Output

$$\bar{F}(x) = F_M(x). \tag{13}$$

Once all M iterations have been completed, the $F_M(x)$ function will have been updated, then the The final model, $\bar{F}(x)$, will approximate the connection between the independent and the response variables.

2.9. Hausman test (Choosing between fixed and random effects)

To decide between a fixed or random effect model for panel data, the most widely used test is the Hausman test. It basically tests whether the unique errors are correlated with the regressors or not. Basically, it has the hypothesis that,
H_0: The random effects model is appropriate.
H_1: The fixed effects model is appropriate.
Generally, when the p-value is less than 0.05, then the fixed effect model is chosen over the random effect model.

2.10. Homoscedasticity test

This assumption states that, the probability distribution of error terms remains the same over all observations of the independent variables. The study used the Studentized Breusch−Pagan (PB) test. The BP test statistic follows a Chi−squared distribution with degrees of freedom based on the number of variables used in the study. It has the hypothesis as;
H_0: There is a constant variance (Homoscedasticity)
H_1: There is non−constant variance (Heteroscedasticity)

When the probability value is below 5% significant level, then we reject the null hypothesis and conclude that there is the presence of heteroscedasticity.

2.11. *Serial correlation test in panel residuals*

Autocorrelation means serial dependence. The Breusch-Godfrey/Wooldridge test for serial correlation in pooled-OLS , fixed effects and random effects panel models was extensively recommended in . This study used the Breusch-Godfrey/Wooldridge test for serial correlation in panel to test for serial correlation. It has the hypothesis as;
H_0: there is no serial correlation.
H_1: there is serial correlation.
For p-value > 0.05, we conclude that there is no serial correlation, if otherwise then we conclude on the alternative hypothesis.

2.12. *Cross-sectional dependency test*

Cross sectional dependency occurs when there is a correlation between the error terms across different units within the same time period. This study used both the Breusch-Pagan Lagrange Multiplier(LM) test of independence and Pasaran cross-sectional dependence (CD) test in testing the contemporaneous correlation. [2] in the study concluded that cross-sectional dependence is a major issue in macro panels with long time series. It has the hypothesis as;

H_0: there is no cross-sectional dependence.

H_1: there is cross-sectional dependence.

When the p-value is less than 0.05 significant level, then we conclude that there is cross-sectional dependence.

Violation of the assumption of serial correlation and heteroscedasticity.

$$Y_t = \beta_0 + \beta_1 X_T + ... + \beta_{r+1} X_{t-r} + \mu_t, \tag{14}$$

where the $\beta_0, \beta_1, ..., \beta_{r+1}$ etc are the coefficients and the $X_T ...., X_{t-r}$ etc are the lags.
Suppose that μ_t is serially correlated, the ordinary least squared (OLS) standard errors are possibly biased, hence a better approach with SEs that are robust to autocorrelation and heteroscedasticity need to be use. The two most widely used estimators are the Blundell−Bond (1998) and the Arellano−Bond(1991) estimators which were developed to handle issues of autocorrelation and heteroscedasticity in panel residuals. This study used the clustered standard error estimates approach which is part of the family of heteroscedasticity and autocorrelation-consistent (HAC) standard errors methods studied extensively in [15]. Consider a generalization of the distributed lag model, where the errors u_t are not necessarily i.i.d. The clustered standard errors are part of HAC which is use in calculating standard errors that accounts for potential correlations between observations within groups or clusters.

2.13. *Model evaluation techniques*

The study used the following model evaluation techniques in accessing the performance accuracy of the models.

2.13.1. R-squared (R^2)

Coefficient of determination (R-squared (R^2)) is a statistical measure that provide information about the goodness of fit of a model. It has the mathematical form as;

$$R^2 = 1 - \frac{SSR}{SST}, \tag{15}$$

which is same as;

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \tag{16}$$

where SSR represent the sum of squared regression, SST denotes the sum of squared total.

2.13.2. Mean squared error (MSE)

MSE accounts for the average squared difference between the expected and actual values of the target variable. Mathematically, it is denoted as;

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y}_I)^2, \tag{17}$$

where n is the number of observation in the training dataset, $\bar{Y}_i$ is the predicted value and Y_i is the actual value.

2.13.3. Root mean squared error (RMSE)

It is the mean squared error between the values predicted by the model and the true outcome values that were observed. Mathematically, it is represented as;

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2}{n}}, \tag{18}$$

where n is the number of observation in the training dataset, $\bar{Y}_i$ is the predicted value and Y_i is the true value.

2.13.4. Mean absolute percentage error (MAE)

This measures the error in percentage form. It is the mean absolute discrepancy between actual and anticipated results. Often it is less sensitive to outliers as compared to RMSE. Mathematically, it is represented as;

$$MAPE = \frac{\sum_{i=1}^{n}|Y_i - \bar{Y}_I|}{n} \times 100, \tag{19}$$

where n is the number of observation in the training datasets, $\bar{Y}_I$ is the predicted value and Y_i is the true value.

2.14. Results and Discussion

The study used the median approach in filling the missing values in the data since median is not affected by outliers hence gives accurate results for this data than the mean.

Table 1. Descriptive statistics

Variable	Obser.	Mean	Std. Dev.	Kurtosis	Skewness
UNEMP	1470	9.1075	7.4835	−0.0431	0.970
GOVCONS	1470	12.1502	8.2250	1.23	0.580
FINCONS	1470	83.5272	15.5114	1.86	−0.669
FDI−OUT	1470	0.9418	8.7759	301.00	-1.68
FDI−IN	1470	3.9347	9.2477	92.40	6.88
AGRIC	1470	20.5937	12.7926	0.739	0.676
INF	1470	39.1559	717.0250	1313.00	35.50
POPG	1470	2.3768	1.3355	75.1	−2.79
PWKR	1470	5.3801	16.1672	144.00	9.35
EXR	1470	4.574×10^6	1.754×10^8	1465.00	38.3
CAB	1470	−4.8052	10.1076	33.70	−2.55
TRD	1470	62.5699	33.4181	15.90	2.62
Gross−savings	1470	19.1010	10.6027	2.35	0.777

2.15. Descriptive statistics

Table 1 and Table 2 presents the descriptive statistics for all the variables in the data. For the 49 African countries selected, fourteen (14) are East African countries, nine (9) Central African countries, five (5) North Africa countries, sixteen (16) West African countries and five (5) Southern African countries. The normality of the variable distribution is evaluated using the skewness and kurtosis measurements.
From Table 1 and Table 2, unemployment rate had an average of 9.1075% with a standard deviation of 7.4835. The highest and least unemployment rates were 37.852% and 0.316% recorded by Eswatini in 2022 and Niger in 2011 respectively. Unemployment rate was positively skewed with value of 0.970 and platykurtic with excess kurtosis of −0.0431. On the other hand, government final consumption expenditure had a mean of 12.1502% with a standard deviation of 8.2250. The highest value of government final consumption expenditure was 50.8365% recorded by Libya in 2015. It was positively skewed with a skewness value of 0.580 and platykurtic in nature (has excess kurtosis of 1.23).

Population growth rate averaged of 2.3768% with a standard deviation of 1.3370. It was Negatively skewed (skewness of −2.78) and leptokurtic (kurtosis of 74.80). The maximum value was 16.7500% recorded by Rwanda in 1996 and the least value was -17.9882% recorded by Rwanda in 1995. On the other hand, personal remittances averaged 5.3801%. It is positively skewed (skewness value of 9.35) and leptokurtic (kurtosis of 144). The maximum value (342.7%) for personal remittances received was recorded by Djibouti in 2023.
However, agricultural had a mean of 20.5937% with a standard deviation of 12.7926. It had skewness value of 0.676 (positively skewed) and a kurtosis of 0.739 (platykurtic). It's maximum value was 79.0424%, recorded by Liberia in 2002 whilst Equatorial Guinea recorded the minimum value of 0.8927% in 2008. Inflation had a mean value of 39.1559% with a standard deviation of 717.0755. It was positively skewed with value of 35.5 and a high positive kurtosis of 1312 making it leptokurtic in nature.
But inflation had a highest value of 26762% which was recorded by Dem. Republic of Congo in 1994 and had a least value of −31.5659% recorded by Equatorial Guinea in 1998.

Table 2. Descriptive statistics (continued)

variable	Minimum value	Minimum country	Minimum year	Maximum value	Maximum country	Maximum year
UNEMP	0.316	Niger	2011	37.852	Eswatini	2022
GOVCONS	0.1395			50.8365	Libya	2015
FINCONS	16.7130	Equatorial Guin.	2005	148.5079	Rwanda	1994
FDI−OUT	−202.8239	Liberia	1998	167.3292	Liberia	1997
FDI−IN	−82.8921	Liberia	1996	161.8238	Equatorial Guin.	1996
AGRIC	0.8927	Equatorial Guin.	2008	79.0424	Liberia	2002
INF	−31.5659	Equatorial Guin.	1998	26762.0183	Dem. Rep. Congo	1994
POPG	−17.9882	Rwanda	1995	16.7500	Rwanda	1996
PWKR	0			342.7024	Djibouti	2023
EXR	6×10^{-5}	Angola	1994	6.723×10^{9}	Zimbabwe	2008
CAB	−147.9973	Equatorial Guin.	1996	43.3987	Angola	1996
TRD	0			347.9965	Djibouti	2013
Gross−savings	−19.9030	Cote d'Ivoire	2007	67.9020	Libya	2006

Table 3. Stationarity test of variables (Augmented Dickey-Fuller (ADF) test)

Variable	Test Statistic	p−value	Order
UNEMP	−6.3012	0.01 ***	I(0)
GOVCONS	−8.4525	0.01 ***	I(0)
FINCONS	−9.6263	0.01 ***	I(0)
FDI−OUT	−56.7800	0.01 ***	I(0)
FDI−IN	−21.7580	0.01 ***	I(0)
AGRIC	−7.2229	0.01 ***	I(0)
INF	−37.0000	0.01 ***	I(0)
POPG	−19.5910	0.01 ***	I(0)
PWKR	−31.7680	0.01 ***	I(0)
EXR	−38.3900	0.01 ***	I(0)
CAB	−16.8820	0.01 ***	I(0)
TRD	−14.0000	0.01 ***	I(0)
Gross−savings	−12.3680	0.01 ***	I(0)

2.16. Stationarity test

This study assessed the stationarity of the variables with both the augmented Dickey-Fuller (ADF) test and the Fishers type panel unit root test.
From Table 3, individual variables were extracted and stationarity tested on them using the augmented Dickey-Fuller (ADF) test. From the Table 3, the p-value of all the variables are less than 0.05 significant level, which indicates that all the variables used in the study are stationary at levels. This gives an evidence that the results of the analysis may not be spurious.

Also from Table 4, the p-value of the overall panel-ADF test for the panel unit root test is 5.3134×10^{-38}, which is less than 5% significant level, hence the null hypothesis is rejected and concluded that there is no unit root. The individual Fisher-type panel unit root test for stationarity for each variables also had a significant test statistic (p-value¡0.05 significance level) hence confirming the ADF test of integration of order zero (0).

Table 4. Fisher-type panel unit root test for Stationarity (Chois test)

Variable	Test Statistic	$p-$value	Order
Overall Panel-ADF test	-1.283363×10^{1}	5.3134×10^{-38} ***	I(0)
Individual Variables p-values			
UMP		3.5275×10^{-9} ***	I(0)
CAB		1.0000×10^{-16} ***	I(0)
ER		1.3834×10^{-16} ***	I(0)
FDI		1.0000×10^{-16} ***	I(0)
PopG		1.0000×10^{-16} ***	I(0)
GOVCONS		2.1343×10^{-12} ***	I(0)
PWKR		1.0000×10^{-16} ***	I(0)
Trade		1.0000×10^{-16} ***	I(0)
INF		1.0000×10^{-16} ***	I(0)
AFF		1.2013×10^{-10} ***	I(0)
FINCONS		3.8293×10^{-13} ***	I(0)
Gross−savings		1.0000×10^{-16} ***	I(0)
FDI−IN		1.0000×10^{-16} ***	I(0)

Table 5. Some test performed

Test performed	F-statistic	Chi-square	$p-$value
Poolability test	118.29		2.200×10^{-16} ***
Breusch-Pagan LM time fixed effects test		10.559	0.001156 ***
Breusch-Pagan LM individual fixed effects test		10712	2.200×10^{-16} ***
Gourieroux, Holly and Monfort LM two-ways test		10723	2.20×10^{-16} ***

2.17. *Checking if the pooled ordinary least squares (Pooled OLS) model and other forms of fixed effects models are suitable for the data.*

From Table 5, since the p-value of the test is less than 5% significant level, hence the null hypothesis is rejected and it is concluded that the pooled OLS method is not good for the data. Hence, this study used only the fixed effects and random effects models.

From Table 5, the p-value of the Breusch-Pagan Lagrange Multiplier test for time fixed effects is less than 0.05 significant level, hence the null hypothesis is rejected indicating that the time fixed effects model is good for the data.

From Table 5, the p-value of the Breusch-Pagan Lagrange Multiplier test for individual fixed effects is less than 0.05 significant level hence the null hypothesis is rejected indicating that the time fixed effects model is good for the data.

Similarly from Table 5, the Gourieroux, Holly and Monfort Lagrange Multiplier test for two-ways effects revealed that the two-ways fixed effects model is good for this data.

Since the three forms of fixed effect models tested in this study revealed that they are suitable for the data hence, the study chose both the individual fixed effect model and the individual and time specific fixed effects model for the analysis.

Table 6. Serial correlation testing in panels residuals

Test	Chi− squared	*p*− value
Breusch-Godfrey/Wooldridge test	1051.1	2.200×10^{-16} ***

Table 7. Homoscedastic test

Test	BP test statistic	*p*− value
Studentized Breusch−Pagan test	72.648	1.020×10^{-10} ***

2.18. Fixed Effects and Random Effects Models

Implementation of the models

The plm package in r software was used in implementing the various traditional models. Under the fixed effect model, two forms out of the three possible ways of implementation were used. These are the individual-specific effects and the two-ways (individual and time effects) approaches were used.

Fixed and random effects models for unemployment rate on the independent variables were fitted. Before results of the fixed and random effects models can be used for inference, there should not be serial correlation in the residuals of the models and the residuals variance should be constant over time. The regression model diagnostic were therefore done to investigate that. Serial correlation and homoscedasticity tests were performed and the results presented in Table 8 and Table 9.

2.18.1. Serial correlation testing in panels

Serial correlation is a major issue with macroeconomic variables. From Table 8, the p-value of the test is 2.200×10^{-16} which is less than 5% significant level. This confirms that there is serial correlation in the panels model residuals. This shows that the fixed and random effect results initially fitted cannot be used to make inference.

2.18.2. Homoscedasticity test in panel residuals

Homoscedasticity test was performed on the model. This assumption states that, the probability distribution of errors terms remains the same over all observations of the independent variables.
From Table 9, the p-value of the test is 1.020×10^{-10} which is less than 5% significant level. This confirms that the null hypothesis is rejected and concluded that there is non−constant variance.

Since the error terms associated with the initial fixed and random effects models are autocorrelated and heteroscedastic, the models cannot be used for further analysis hence, an adjustment was made.

Table 8. Hausman test result

Item	Differences in coefficients
Chi− squared	2472.80
$p-$ value	2.20×10^{-16} ***

Table 9. Cross−sectional dependence testing in panels

Test	Chi− Squared	$z-$value	$p-$value
Breusch-Pagan LM test	7581		2.20×10^{-16} ***
Pesaran CD test		11.201	2.20×10^{-16} ***

2.19. Test for selecting between fixed effects and random effects models

2.19.1. Hausman test

To decide between fixed or random effect model for a panel data, the common test often used is the Hausman test.
From Table 6, the p-value is 2.20×10^{-16} which is less than 5% significant level, hence the fixed effect model is selected over the random effect model. The result showed a low p-value of the test, which indicates that the null hypothesis is rejected saying that the individual random effects are exogenous, thus making the random effects model inconsistent for the data. Hence, this study used the fixed effect model to perform subsequent analysis.

2.19.2. Cross-sectional dependence testing in panels

The study used both the Breusch−Pagan lagrangian multiplier (LM) test of independence and Pasaran cross−sectional (CD) test in testing the contemporaneous correlation. The tests were used to determine whether the residuals are correlated across entities.
From Table 7, the p-value for both Breusch−Pagan Lagrange multiplier(LM) test and Pasaran cross−sectional dependence (CD) test for cross−sectional dependence in panels are 2.20×10^{-16} which is less than 5% significant level. This confirms that there is cross sectional dependency across entities.

2.20. Fixed effects and random effects models using robust clustered standard errors estimate approach

In this section, a more robust approach was used to model unemployment base on the covariates. Since there exist serial correlation and heteroscedasticity in the error terms of the initial fixed and random effects models, the earlier results are not good for inference.
The plm package in r software was used in implementing the various models. This study used the robust clustered standard error estimator approach, which is part of the heteroscedasticity and autocorrelation−consistent (HAC) standard errors technique [16].The study further used functions like co-

eftest() in conjunction with vcovHC() from the package sandwich, with type in the code set to HC1 (type 1 error) in deriving the clustered standard errors. Conveniently, vcovHC() recognizes panel model objects, thus objects of class plm and computes the clustered standard errors by default.

Country−specifics or One−way fixed effect regression model.

From Table 10 and Table 11, under the country−specific effects, only the inflation rate (INF) was a significant determinant of unemployment rate at 5%. It had a negative relationship with unemployment (coefficient value of -5.2244×10^{-3} and a p-value of 0.0449). This means that, on average, holding all factors constant, an increase in inflation will lead to a reduction in the unemployment rate.

Again, agriculture was significant at 1% with a coefficient value of 7.3041×10^{-2} and a p-value of 0.0764. Agriculture had a positive relationship with unemployment, which may be due to the fact that most people engage in agricultural activities for domestic use rather than commercial use.

From Table 10 and Table 11 under the individual−specific effects, exchange rate, foreign direct investment net outflows, personal remittances, final consumption expenditure, gross savings, and foreign direct investment net inflows all have a negative relationship with unemployment rate, though are statistically insignificant since their p-value is greater than 5% significant level. On the other hand, current account balance, population growth, government final consumption expenditure, and trade openness all have a positive relationship with the unemployment rate, but are all statistically insignificant.

Country and time specific or Two−ways fixed effect regression model.

Table 10 and Table 11, under the country and time-specific effects, only the inflation rate (INF) is significant at 5% significant level. It had a negative relationship with unemployment, with a coefficient value of −0.0058 and a p-value of 0.0215. Similarly, gross savings had a negative relationship with unemployment, a coefficient value of −0.0860 and a p-value of 0.0909 making it significant at only 10% significant level.

From the result current account balance, foreign direct investment net outflow, personal remittances and final consumption expenditure had a negative relationship with unemployment rate but are all statistically insignificant. But on the other hand, exchange rate, population growth, government final consumption expenditure, trade, agriculture and foreign direct investment net inflow all have a positive relationship with unemployment rate though are statistically insignificant.

Random effects regression model.

From Table 10 and Table 11 under the random effects model, current account balance had a positive relationship with unemployment and statistically significant with a coefficient value of 1.0796×10^{-1} and a p-value of 2.217×10^{-5}.

Exchange rate had a negative relationship with unemployment and statistically significant with a coefficient value of -1.5987×10^{-2} and a p-value of 3.088×10^{-9}. Similarly, population growth also had a negative relationship with unemployment rate but statistically significant with a coefficient value of -1.9270×10^{-1} and a p-value of $3.944 \times 10-5$. The negative relationship means that an increase in them leads to a reduction in unemployment rate.

From Table 10 and Table 11 under the random effects model, trade had a positive relationship with unemployment but statistically significant with a coefficient value of 9.9486×10^{-2} and a p-value of 3.452×10^{-5}. Similarly, inflation rate had a positive relationship with unemployment rate and statistically significant with a coefficient value of 3.1795×10^{-2} and a p-value of 7.687×10^{-7}. This shows that an increase in inflation will leads to a rise in the unemployment rate.

Agriculture is statistically significant and had a negative relationship with unemployment rate with a coefficient value of -4.5621×10^{-1} and a p-value of 2.20×10^{-16}. This shows that on average, holding all other

Table 10. Fixed effects and random effects models using robust clustered standard errors

Variable	Individual−specific fixed eft	Random eft
Intercept:		
Coefficient		-1.2215×10^{-16}
Std. Erros		2.0002×10^{-2}
p-value		1.000
CAB:		
Coefficient	9.8636×10^{-4}	1.0796×10^{-1}
Std. Erros	9.1700×10^{-3}	2.5368×10^{-2}
p-value	0.9144	2.217×10^{-5} ***
ER:		
Coefficient	-1.8225×10^{-5}	-1.5987×10^{-2}
Std. Error	3.5742×10^{-3}	2.6807×10^{-3}
p-value	0.9959	3.088×10^{-9} ***
FIDI:		
Coefficient	-2.3107×10^{-3}	-1.0695×10^{-2}
Std. Error	2.3612×10^{-3}	1.8835×10^{-2}
p-value	−0.9786	0.5702
POPG:		
Coefficient	4.8191×10^{-4}	-1.9270×10^{-1}
Std. Erros	6.2493×10^{-3}	4.6733×10^{-2}
p-value	0.9385	3.944×10^{-5} ***
GOVCONS:		
Coefficient	2.1716×10^{-3}	7.8714×10^{-3}
Std. Erros	3.6824×10^{-2}	2.4464×10^{-2}
p-value	0.9530	0.7477
PWKR:		
Coefficient	-7.6834×10^{-3}	2.0051×10^{-2}
Std. Erros	9.0200×10^{-3}	2.4449×10^{-2}
p-value	0.3945	0.4123
TRD:		
Coefficient	7.2691×10^{-3}	9.9486×10^{-2}
Std. Erros	1.7528×10^{-2}	2.3947×10^{-2}
p-value	0.6784	3.452×10^{-5} ***
INF:		
Coefficient	-5.2244×10^{-3}	3.1795×10^{-2}
Std. Erros	2.6020×10^{-3}	6.4040×10^{-3}
p-value	0.0449 ***	7.687×10^{-7} ***

factors constant, a 1% increase in agriculture leads to approximately 45.6% reduction in unemployment rate. Similarly, final consumption expenditure is statistically significant and had a negative relationship with unemployment, with a coefficient value of -9.0694×10^{-2} and a p-value of 0.0152. This confirms that an increase in final consumption will lead to a reduction in the unemployment rate.

Foreign direct investment net inflow had a positive relationship with unemployment rate and was statistically significant with a coefficient value of 7.4460×10^{-2} and a p-value of 0.00017. This shows that an increase in foreign direct investment net inflow will reduce the employment rate.

2.21. Results based on XGBoost, Multilayer Perceptron, and Recurrent Neural Network Algorithms

2.22. XGBoost Results

Parameter selection and algorithm flow for the XGBoost model

The various features and labels of the raw panel data were then standardized using the MinMaxScaler. After that, the data set was then split into a train set (80%) and test set (20%) using the train−test−split method for subsequent model training and evaluation. An XGBoost regressor was then initialized, setting the objective to ”reg: gamma” and trained using the training set. The rounds used were 100, 150, and 200, and round

Table 11. Fixed effects and random effects models using robust clustered standard errors (continued)

Variable	Individual specific fixed eft	Random eft
AGRIC:		
Coefficient	7.3041×10^{-2}	-4.5621×10^{-1}
Std. Erros	4.1188×10^{-2}	3.0241×10^{-2}
p-value	0.0764 **	2.20×10^{-16} ***
FINCONS:		
Coefficient	-4.9850×10^{-2}	-9.0694×10^{-2}
Std. Erros	4.3636×10^{-2}	3.7326×10^{-2}
p-value	0.2535	0.0152 ***
Gross−savings:		
Coefficient	-8.2935×10^{-2}	-1.6998×10^{-2}
Std. Erros	5.1944×10^{-2}	2.9967×10^{-2}
p-value	0.1106	0.5706
FDI−IN:		
Coefficient	-1.9639×10^{-4}	7.4460×10^{-2}
Std. Erros	7.4229×10^{-3}	1.9740×10^{-2}
p-value	0.9789	0.00017 ***
RSS	76.751	856.86
R^2	0.07043	0.4167
F-test	8.89636	
Chi− Squared		1040.87
p-value	2.220×10^{-16}	2.22×10^{-16}

100 converged well and produced a good result.

XGBoost results on country base

From Table 12, Table 13, and Table 14, there are significant country differences in the prediction results of the XGBoost model. From the results, Chad had the least train set MSE of 5.9160×10^{-7}, Comoros had the least test set MSE of 0.0034, Cote d'Ivoire had the least train set MAPE, and Djibouti had the least test set MAPE.

From the results, there is no country that had the most or the least values of measure accuracy; hence, generalisation cannot be made on the country where the model performed better.

Table 12. XGBoost results on country basis

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Algeria	1.9553×10^{-4}	39.9272	0.00045	0.3322
Angola	7.1612×10^{-5}	0.2542	0.00035	0.0233
Benin	1.3495×10^{-6}	0.0261	0.00043	0.1137
Botswana	1.3192×10^{-4}	5.9241	0.00036	0.1022
Burkina Faso	6.6169×10^{-6}	0.5514	0.00045	0.0916
Burundi	1.7172×10^{-6}	0.6094	0.00043	0.1556
Cabo Verde	4.6310×10^{-5}	0.8205	0.00040	0.0651
Cameroon	7.6569×10^{-6}	0.3117	0.00036	0.0895
Central African Rep.	1.2152×10^{-5}	0.0406	0.00043	0.0241
Chad	$\mathbf{5.9160 \times 10^{-7}}$	0.1915	0.00043	0.3844
Comoros	4.9198×10^{-6}	**0.0034**	0.00035	0.0118
Dem. Rep. Congo	7.4408×10^{-6}	0.1655	0.00041	0.0936
Congo, Rep.	1.2525×10^{-4}	1.1979	0.00040	0.0311
Cote d’Ivoire	5.3808×10^{-6}	0.9877	**0.00030**	0.2147
Djibouti	3.9266×10^{-4}	0.0350	0.00057	**0.0063**

Table 13. XGBoost results on country base (continued)

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Equatorial Guinea	2.2785×10^{-5}	0.1021	0.00038	0.0345
Eswatini	2.5385×10^{-4}	16.3639	0.00040	0.0766
Ethiopia	5.0410×10^{-6}	0.1300	0.0005	0.1103
Gabon	1.1120×10^{-4}	0.3288	0.00042	0.0210
Gambia, The	2.0687×10^{-5}	0.4208	0.00038	0.0635
Ghana	1.3721×10^{-5}	2.5868	0.00036	0.2274
Guinea	7.4343×10^{-6}	0.0563	0.0004	0.0293
Guinea-Bissau	3.6281×10^{-6}	0.0410	0.00047	0.04824
Kenya	5.3254×10^{-6}	0.0094	0.00044	0.0233
Lesotho	8.6101×10^{-5}	0.8457	0.00042	0.0402
Liberia	3.0170×10^{-6}	0.0189	0.00047	0.0411
Libya	1.0499×10^{-4}	0.2609	0.00039	0.0219
Madagascar	5.0566×10^{-6}	1.0043	0.00042	0.7600
Malawi	1.0466×10^{-5}	0.1836	0.0004	0.0762
Mali	1.1229×10^{-6}	0.6357	0.0004	0.1464
Mauritania	3.4118×10^{-5}	0.0920	0.0004	0.0198

Table 14. XGBoost results on country base (continued)

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Mauritius	2.3025×10^{-5}	1.8815	0.0004	0.1374
Morocco	2.8497×10^{-5}	2.3206	0.00038	0.1047
Mozambique	3.1842×10^{-6}	0.0211	0.00045	0.0332
Namibia	1.8600×10^{-4}	12.2035	0.00041	0.1518
Niger	2.0751×10^{-6}	0.1645	0.00041	0.4261
Nigeria	6.6233×10^{-6}	0.2142	0.00042	0.0900
Rwanda	5.2538×10^{-5}	0.2517	0.00041	0.0255
Sao T. and Principe	1.0619×10^{-4}	0.4622	0.00044	0.0359
Senegal	6.2871×10^{-6}	0.0613	0.00037	0.0660
Sierra Leone	4.6146×10^{-6}	0.0671	0.0004	0.0572
South Africa	1.3202×10^{-4}	3.1844	0.00038	0.0446
Sudan	7.2109×10^{-5}	2.0254	0.00044	0.0785
Tanzania	2.7666×10^{-6}	0.0962	0.00042	0.0764
Togo	3.6662×10^{-6}	1.0646	0.00045	0.3186
Tunisia	7.1160×10^{-5}	1.1259	0.00040	0.0639
Uganda	2.2463×10^{-6}	0.2892	0.00033	0.1559
Zambia	6.2162×10^{-5}	3.3083	0.00038	0.1451
Zimbabwe	1.3862×10^{-5}	0.6389	0.00038	0.1108

2.23. MultiLayer Perceptron (MLP) Results

Parameter selection and algorithm flow for the MultiLayer perceptron (MLP) algorithm

The main package used is the RSNNS. In the implementation stage, the various features and labels were then standardized using the MinMaxScaler. After that, the data set was then split into train set and test set using the train−test−split method for subsequent model training and evaluation which were 80% for train and 20% for test.

A multilayer perceptron model containing fully connected and MLP layers was constructed and trained using the training set. During training, the parameters for the initialization function was set to be ”c(-0.3, 0.3)”, the learning function used was ”Std−Backpropagation”, the activation function of the output units was set to linear and the maximum number of iterations to learn was set to 100. Even though other number of iteration were tried 100 converged well and gave a better fit .

MultiLayer perceptron (MLP) country base results.

From Table 15, Table 16 and Table 17, there is no country that had most of the least values of MSE and MAPE. Guinea−Bissau had the least train set MSE of 1.9984×10^{-5}, Malawi had the least test set MSE of 2.9091×10^{-6}, Libya had the least train set MAPE of 0.0113 and Angola had the least test set MAPE of 0.0106. This result confirms that there is no clear evidence to conclude that the model performed better in a particular country. In same countries the model is able to performed better on the unseen data than the seen data as in the case of Lesotho which had test for both MSE and MAPE as 0.0185 and 7.7884×10^{-5} with their respective train set of 2.5603×10^{-4} and 0.0224.

Table 15. MultiLayer perceptron results on country base

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Algeria	4.2199×10^{-2}	3.0976×10^{-2}	0.4617	0.4755
Angola	2.3129×10^{-4}	2.6802×10^{-5}	0.0231	**0.0106**
Benin	1.9136×10^{-4}	7.6836×10^{-5}	0.5307	0.3968
Botswana	3.1455×10^{-3}	5.2855×10^{-3}	0.0942	0.1187
Burkina Faso	6.0512×10^{-4}	8.5306×10^{-4}	0.2538	0.2616
Burundi	5.9283×10^{-4}	4.4681×10^{-4}	0.6795	0.5526
Cabo Verde	5.4287×10^{-4}	1.1283×10^{-3}	0.0604	0.0933
Cameroon	2.7136×10^{-3}	2.0057×10^{-3}	0.3376	0.30843
Central African Rep.	1.1443×10^{-4}	1.2305×10^{-4}	0.0494	0.0570
Chad	4.2537×10^{-5}	1.1765×10^{-5}	0.3038	0.2140
Comoros	1.9749×10^{-4}	2.9890×10^{-4}	0.0776	0.0874
Congo, Dem. Rep.	3.9399×10^{-4}	2.3323×10^{-4}	0.1975	0.1529
Congo, Rep.	$3.4673 \times 10{-}4$	5.9980×10^{-5}	0.0231	0.0124
Cote d'Ivoire	1.8407×10^{-3}	2.8557×10^{-3}	0.3814	0.4307
Djibouti	1.5077×10^{-4}	1.7746×10^{-4}	0.0149	0.0164

Table 16. MultiLayer perceptron results on country base (continued)

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Equatorial Guinea	9.3774×10^{-5}	8.8058×10^{-5}	0.0275	0.0343
Eswatini	1.1449×10^{-2}	2.9063×10^{-2}	0.0991	0.1488
Ethiopia	2.1500×10^{-4}	1.1796×10^{-4}	0.1952	0.1272
Gabon	1.5534×10^{-3}	1.1280×10^{-3}	0.0761	0.0619
Gambia, The	3.0943×10^{-3}	2.0662×10^{-3}	0.2804	0.2139
Ghana	3.7615×10^{-3}	3.3108×10^{-3}	0.4709	0.5570
Guinea	1.0405×10^{-4}	6.0903×10^{-5}	0.0600	0.0556
Guinea-Bissau	$\mathbf{1.9984 \times 10^{-5}}$	2.9107×10^{-5}	0.0522	0.0610
Kenya	7.2736×10^{-4}	1.1678×10^{-3}	0.2107	0.2411
Lesotho	2.5603×10^{-4}	7.7884×10^{-5}	0.0224	0.0185
Liberia	1.8702×10^{-4}	7.9623×10^{-5}	0.1736	0.1416
Libya	5.9036×10^{-5}	5.4667×10^{-5}	**0.0113**	0.0127
Madagascar	1.9479×10^{-3}	2.6736×10^{-3}	0.6903	3.2082
Malawi	3.5660×10^{-5}	$\mathbf{2.9091 \times 10^{-6}}$	0.0320	0.0124
Mali	2.2567×10^{-4}	3.9810×10^{-4}	0.1541	0.2001
Mauritania	1.0863×10^{-4}	4.4718×10^{-4}	0.0307	0.0199

Table 17. MultiLayer perceptron results on country base (continued)

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Mauritius	9.1151×10^{-4}	6.0510×10^{-4}	0.1374	0.1004
Morocco	2.6984×10^{-3}	1.8003×10^{-3}	0.1727	0.1550
Mozambique	9.8779×10^{-5}	7.0692×10^{-5}	0.1093	0.0948
Namibia	1.8334×10^{-3}	1.4693×10^{-3}	0.0638	0.0569
Niger	3.9058×10^{-4}	3.4461×10^{-4}	1.2786	1.5614
Nigeria	2.2254×10^{-4}	3.4484×10^{-4}	0.1097	0.1307
Rwanda	6.2056×10^{-4}	2.7623×10^{-3}	0.0367	0.0740
Sao T. and Principe	3.1844×10^{-3}	7.5376×10^{-4}	0.1298	0.0585
Senegal	7.8191×10^{-4}	2.6471×10^{-4}	0.2698	0.2194
Sierra Leone	1.4674×10^{-4}	9.3798×10^{-5}	0.1092	0.0944
South Africa	2.5790×10^{-3}	3.5389×10^{-3}	0.0645	0.0723
Sudan	3.1567×10^{-3}	1.4060×10^{-3}	0.1412	0.0902
Tanzania	1.4692×10^{-4}	6.9359×10^{-5}	0.1531	0.1197
Togo	5.1178×10^{-4}	6.5447×10^{-4}	0.3242	0.4061
Tunisia	1.8734×10^{-3}	5.4776×10^{-4}	0.091	0.0455
Uganda	1.8812×10^{-4}	1.6754×10^{-4}	0.1791	0.1401
Zambia	1.2591×10^{-2}	1.3885×10^{-2}	0.4424	0.4886
Zimbabwe	1.4954×10^{-3}	1.6482×10^{-3}	0.1816	0.1785

2.24. Recurrent Neural Network (RNN) Results

Parameter selection and algorithm flow for the recurrent neural network (RNN) algorithm
The main package used is the RNN. The various features and labels in the raw panel data were then standardized using the MinMaxScaler. The data set was then divided into train set (80%) and test set (20%) using the train−test−split method for subsequent model training and evaluation. The learning rate applied for weight iteration was set to be 0.01, the dimensions of hidden layers was set to (10,2), the learning rate decay was set to 1, the output activation function was set to linear, the loss function was set to L1 (lasso) and the number of epoch was set set to 250. The other parameter values tried revealed the existence of overfitting and underfitting.

RNN country base results
From Table 18, Table 19 and Table 20, Rwanda had the least train set MSE of 0.0371, Angola had the least test set MSE of 0.0101, Rwanda had the least train set MAPE of 13.4878 and Angola had the least test set MAPE of 8.6181. The model is able to perform well on the unseen data of Angola than any other countries. However, the high MSE and MAPE values on the test set indicate that the model is at risk of overfitting when faced with new data.

Table 18. RNN results on country base

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Algeria	0.1230	0.0952	32.9352	30.1656
Angola	0.0441	**0.0101**	14.8213	**8.6181**
Benin	0.0701	0.0326	22.1083	15.8675
Botswana	0.0707	0.1176	22.6591	27.8282
Burkina Faso	0.0975	0.1252	26.7236	29.5331
Burundi	0.1618	0.1183	38.7363	33.2700
Cabo Verde	0.0476	0.0968	18.8529	26.9413
Cameroon	0.1295	0.0882	34.96091	26.1528
Central Africa Rep.	0.0706	0.0732	21.4031	24.0547
Chad	0.0594	0.0206	19.4658	11.5182
Comoros	0.0792	0.1124	21.6727	27.5364
Con,Dem.Rep	0.0976	0.0558	28.8281	22.5950
Congo, Rep.	0.0544	0.0165	17.6498	10.6184
Cote d'Ivoire	0.0845	0.1272	25.1936	33.8948
Djibouti	0.0908	0.1274	27.4710	34.9097

Table 19. RNN results on country base (continued)

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Equatorial Guinea	0.0654	0.0682	21.3454	24.5249
Eswatini	0.0622	0.1446	18.8061	29.5533
Ethopia	0.0983	0.0543	27.3721	18.5075
Gabon	0.1143	0.0767	32.1991	25.1495
Gambia	0.1074	0.0716	30.1271	26.0121
Ghana	0.0756	0.0648	22.6810	24.1499
Guinea	0.0612	0.0341	18.9830	16.1446
Guinea Bissau	0.0562	0.1040	17.9187	24.071
Kenya	0.1049	0.1585	27.2833	33.3864
Lesotho	0.0569	0.0264	18.0124	13.3377
Liberia	0.0675	0.0281	21.5393	15.3148
Libya	0.0680	0.0670	22.0724	23.4603
Madagasca	0.0893	0.1077	26.0354	25.9016
Malawi	0.1081	0.0788	30.1261	27.3876
Mali	0.0631	0.0819	20.2848	24.35429
Mauritania	0.0543	0.0230	18.0274	11.9481

Table 20. RNN results on country base (continued)

Country	Train−MSE	Test−MSE	Train−MAPE	Test−MAPE
Mauritius	0.1031	0.0727	28.6953	22.9846
Morocco	0.1421	0.0876	34.1690	27.5209
Mozambique	0.0776	0.0516	23.8717	20.3588
Namibia	0.0442	0.0385	17.2055	15.7815
Niger	0.0693	0.0706	20.7152	22.4931
Nigeria	0.0468	0.0694	16.3296	21.2083
Rwanda	**0.0371**	0.1395	**13.4878**	24.7188
Sao T.and Prince	0.1688	0.1517	37.6928	38.0842
Senegal	0.0675	0.0261	21.4125	14.9577
Sierra Leone	0.0942	0.0571	25.8836	21.7557
South Africa	0.0883	0.1601	24.7024	38.3493
Sudan	0.0467	0.0232	18.5147	13.3152
Tanzania	0.0687	0.0333	21.3718	16.5372
Togo	0.1443	0.1792	35.5765	41.1584
Tunisia	0.0737	0.0188	21.5435	10.4838
Uganda	0.0660	0.0628	21.8613	21.1117
Zambia	0.0849	0.0967	25.6588	30.2259
Zimbabwe	0.0676	0.0679	20.9995	20.9510

Table 21. Cross−validation accuracy results for the utilized deep learning algorithms

Model	Tr−Cor	Test−Cor	Tr−MSE	Test−MSE	Tr−MAPE	Test−MAPE
RNN	0.6103	0.5727	0.0298	0.0319	14.3860	14.9103
MLP	0.6844	0.6673	**0.00036**	**0.0233**	**10.6628**	**11.2002**
XGBoost	**0.9996**	**0.9408**	0.0488	6.8362	11.5750	150.6152

Table 22. Comparing of the two best models

Model	Mean Square error	Root mean square error
MLP	**0.00036**	**0.01892**
Fixed Effects	0.05221	0.22850

Comparing of Models Performances

From Table 21, the MLP model had a train-test correlation of 0.6844 and a test set correlation of 0.6673, which are all higher than 5% significant level, indicating a very good relationship between the actual and predicted values. It had the least train set MSE of 0.00036, the least test set MSE of 0.023, the least train set MAPE of 10.6628, and the least test set MAPE of 11.2002. The least MSE and MAPE generally mean that there is a good predictive model as compared to the other models. The MLP model is the overall best model among the three machine learning models used in the study
From Table 21, the XGBoost model had the highest correlation value for both the train and test sets of 0.9996 and 0.9408, respectively. This shows that there is a very strong positive relationship between the actual values and the predicted values.

Comparison of fixed effects model and multilayer perceptron model

From Table 22, MLP had the least MSE of 0.00036 and RMSE of 0.01892. This indicates that the multilayer perceptron is the overall best model for modeling the impact of the selected covariates on unemployment rate in Africa. This also indicates the superiority of the machine learning models over the traditional longitudinal models.

2.25. Variable importance analysis of independent variables on unemployment rate in Africa

In this part of the study, a further analysis was done to investigate how significant the independent variables used affect the unemployment rate in Africa using the variable importance analysis.

2.26. MLP variable importance plot

Figure 1 is the variable importance plot for the MLP model. Although the plot does not give the exact quantitative magnitude (percentage) in which each feature contributes to unemployment, the nature of their relationship (negative or positive) with unemployment is identified. Agriculture contributed greatly to the unemployment rate in Africa since it has a long history. From the plot, it had a negative relationship with unemployment. This shows that an increase in agricultural activities results in a decrease in the

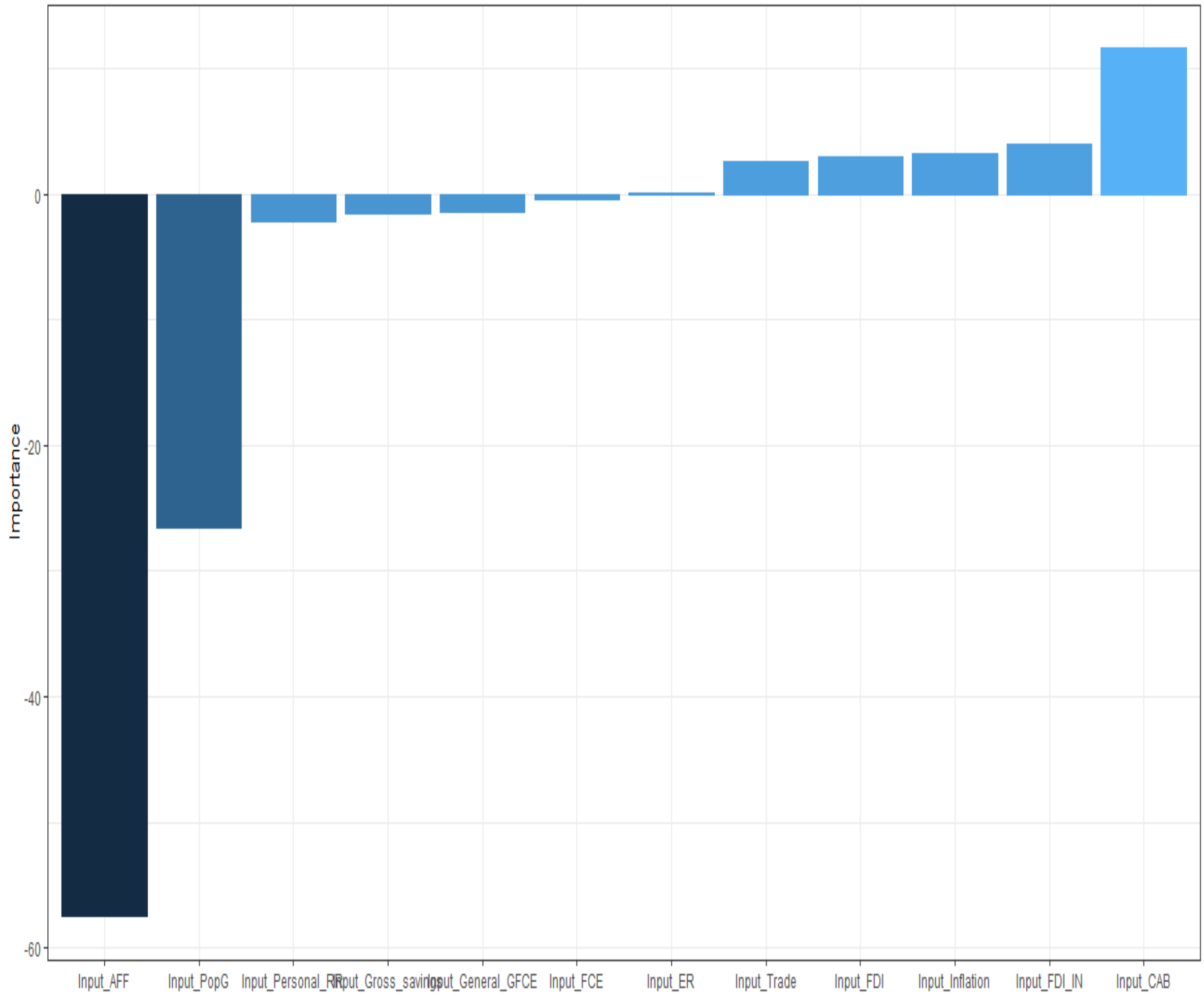

Figure 1. MLP variable important plot

unemployment rate. This was followed by population growth, which also had a negative relationship with unemployment. The third most impactful variable was the current account balance, which had a positive relationship with unemployment.

3. XGBoost variable importance

Since the XGBoost model also performed well in terms of the correlation, variable importance analysis was also done on it. Table 23 showed the variable importance results for the XGBoost model. The result gave the various percentages in which each variable contributes to unemployment, but is not able to determine if there exists a negative or positive relationship between the independent variables and unemployment. From Table 23, agriculture, forestry, and fishing (value added % GDP) had the highest value of gains, which is 0.5312. This shows that under the XGBoost model, agriculture significantly determines the unemployment rate in Africa, which is a confirmation of earlier results by the MLP variable importance analysis. On the list, official exchange rate (LCU per US $, period average) came as the second highest contributor to unemployment rate, followed by population growth.

Table 23. XGBoost variable importance

Variables	Gain	Frequency
AGRIC	0.5312	0.0965
EXR	0.1415	0.1181
POPG	0.0899	0.1019
General−GFCE	0.0564	0.0971
PWKR	0.0545	0.1002
TRD	0.0241	0.0681
Gross−savings	0.0203	0.0420
FINCONS	0.0193	0.0517
FDI−OUT	0.0178	0.0761
INF	0.0176	0.0733
CAB	0.0146	0.1133
FDI−IN	0.0128	0.0616

4. Discussion of Results and Conclusions

4.1. Discussion of Results

From the result, multilayer perceptron (MLP) model was identified as the overall best model. Based on the variable importance results, it showed that agriculture, forestry, and fishing, value added as percentage of GDP significantly impact unemployment rate with the long bar. From the results, it had a negative relationship with unemployment rate. This implies that, an increase in agriculture activities in Africa results in a decrease in unemployment rate. This contradicts the result of [5] which detected a positive relationship between agriculture and unemployment rate in the Sub−Saharan Africa countries. Again, this result is in line with [20] which found out that there is a significant impact of agricultural productivity proxy to total GDP in Nigeria. The study revealed that there is a negative relationship between unemployment rate and agricultural productivity proxy to total GDP in Nigeria.

Population growth (annual %) was the second most impacting feature which had a negative relationship with unemployment. This contradict the work of [17] who findings revealed that there is a positive relationship between unemployment rate and population growth in Nigeria. This again, contradict the work of [4]

which detected a positive relationship between population and unemployment.
The third most influencing feature is the current account balance (% of GDP) which had a positive relationship with unemployment in Africa.

In generalization, the MLP model performed better than all the other models since it had the least values of both MSE and MAPE. This conforms to the work of [14] which detected that multilayer perceptron model outperformed in terms of prediction performance over the convolutional neural network (CNN), long short−term memory network (LSTM) and as well as the traditional linear model. On the other hand, the result contradict the work of [10] which found out that the XGBoost model was the overall best model in modeling the panel data which focused on the quarterly GDP panel data of 31 provinces and cities in China.

5. Conclusions

The main aim of the study was to investigate the impact of the selected macroeconomic factors on unemployment rate in Africa.
The random effect model was fitted. The results revealed that, eight (8) of the variables used were significant at 5%. Current account balance, trade, inflation rate and foreign direct investment (net inflows) had a positive relationship with unemployment. On the other hand population growth, agriculture, exchange rate and final consumption expenditure (% of GDP) had a negative relationship with unemployment.

Three machine learning models, thus the XGBoost, RNN and the MLP models were also fitted to determine the impact of the macroeconomic variables on unemployment rate. From the results, the XGBoost model worked well when considering the correlations whiles the MLP model worked excellently when considering the modeling errors for both training and testing data sets (MLP had the least MAPE and MSE for both training and testing data set)

The MLP model is therefore chosen as the best model out of all the fitted models in this study. From the variable importance analysis with the MLP model, the most significant variable that had high impact on unemployment rate was the agriculture, forestry, and fishing, value added as percentage of GDP. This conforms to the claim made by many scholars that Africa employment is dominated by the agriculture sector which can either reduce or increase unemployment. This is followed by population growth (annual %). These two features have an inverse relationship with unemployment.

Based on the findings of this study, the following recommendations are made;

1. This study recommend policy makers to improve upon the agriculture sector by using modern equipment and implement better policies such as incentives to youth in agriculture to help boost productivity since it had the highest impact on unemployment in Africa.

2. Policy makers needs to formulate better policies such as incentives for few families and restrictions on the maximum number of children a family can have to regulate population growth and reduce unemployment.

3. Finally, on the basis of future studies, this study recommend that future studies can develop other machine learning models that are able to capture the features of a panel data.

Conflict of Interest

The authors declare there is no existing conflict of interest.

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